Highly accelerated DCE-MRI using Region of Interest Compressed Sensing

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Target Audience: The current work is relevant to researchers working in the MR community interested in DCE-MRI reconstruction methods and its applications.

Introduction: Dynamic Contrast Enhanced Magnetic Resonance Imaging (DCE-MRI) is used to acquire high contrast images to qualitatively analyze and quantitatively examine MR properties of the tissue such as T_1, Magnetization Transfer (MT), and Pharmacokinetic (PK) maps: K^{trans} (min^{-1}) and K_{ep} (min^{-1}) where, K^{trans} is the flow of Contrast Agent (CA) from plasma to Extravascular Extracellular Space (EES) and K_{ep} is the flow of CA from EES to plasma, which are useful in analysis of cancerous tissues [1]. Compressed Sensing (CS) is a reconstruction technique that reconstructs data from highly undersampled measurements to achieve acceleration in acquisition time [2]. A technique called Region Of Interest Compressed Sensing (ROICS) has been shown to achieve superior CS performance by limiting the sparsity and data consistency objectives of CS to a Region Of Interest (ROI) [3, 4]. Current work applies and compares CS and ROICS reconstruction techniques on DCE-MRI data.

Theory: Conventional CS can be represented by equation: $min_m (|| F_U(m) - y ||_2 + \lambda || \psi(m) ||_1)$ (1), where, m is the current estimate of the DCE image at time point to be obtained, F_u is the undersampled orthonormal Fourier operator: $F(.)$* undersampling mask, y is the undersampled k-space measured by the acquisition process, λ is the regularization factor, determined by methods like Tikhonov regularization or L-curve optimization, Ψ is the sparsifying transform operator and $||.||_k$ is the k-norm operator. Data consistency term was evaluated in the spatial domain and ROICS equation was derived by weighting the spatial data consistency term over a ROI and this results in equation (2), $min_m (|| F^{-1}(F_u(m) - y) * W ||_2 + \lambda || \psi (m * W)||_1)$ (2), where, F^{-1} is the inverse Fourier transform and W is the Ns*Ns diagonal matrix containing a spatial weighting that one can use to specify and evaluate a ROI, of the dimensions of the image. The equation for Tofts Model (TM) in time domain is given by $C(t)=K^{trans}e(-K_{ep}t)*C_a(t)$ (3), where, $C(t)$ is the concentration of CA, $C_a(t)$ denotes Arterial Input Function (AIF) in mM and * denotes convolution operation. Data sparsity is the key criterion in CS and CS reconstruction for DCE-MRI involving spatio-temporal correlations show temporal blurring artifact [5] which manipulates PK maps unlike in cardiac MRI where motion is periodic. ROI mask inclusion enhances the data sparsity in each frame which results in better reconstruction of DCE-MRI data without temporal blurring artifacts.

Methods: Seven breast DCE-MRI data used in the study were taken from the cancer imaging archive website Quantitative Imaging Network (QIN) [6], acquired using Siemens 3T TIM Trisystem. Full breast coverage was acquired with a 3D gradient echo-based Time-resolved angiography WIth Stochastic Trajectories sequence (TWIST), TE/TR were 2.9/6.2 ms, 320x320 in-plane matrix size for 28 images. The contrast agent used was Gd (HP-DO3A). T_2 map data was obtained for considering the suspected cancer region by selecting the ROI. CS and ROICS reconstruction techniques were applied on the dataset at chosen acceleration factors of 2x, 3x, 4x, 5x, 8x, 10x, 15x, and 20x. ROI was drawn around the suspected region on the scout image and subsequent images were reconstructed using ROICS method. ROI selected mask was considered as a weighting function to perform ROICS by restricting the reconstruction to ROI which increases sparsity, whereas conventional CS reconstruction was performed for the entire image. Reconstruction error in the ROI selected region was quantified by Normalized Root Mean Square Error (NRMSE) value for the conventional CS and ROICS reconstructed images. K^{trans} and Ve (Volume Fraction) maps were obtained (only for the ROI selected region) for the images reconstructed using CS and ROICS methods using TM.

Figure 1(a): Representative frame of dataset
1(b): Magnified region of the ROI

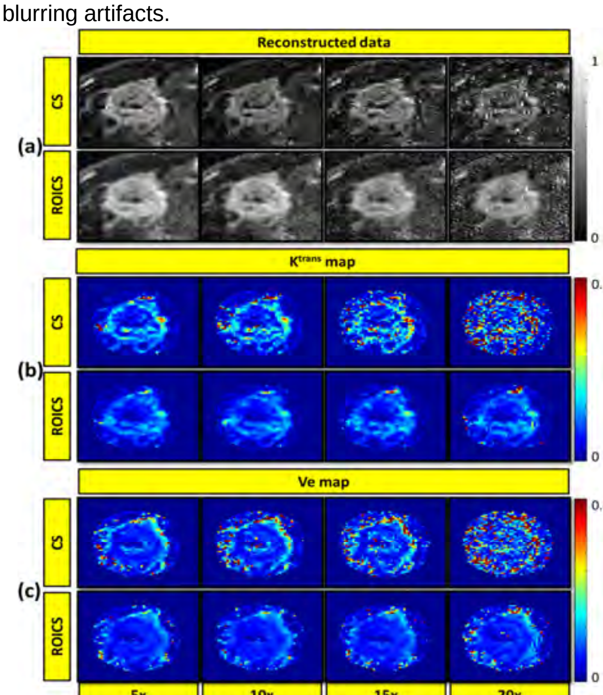

Figure 2: Comparison of CS and ROICS performance; k^{trans} and Ve maps at different acceleration factors.

Results and Discussion: Figure 1a represents the 8th frame of the dataset (post contrast) and the ROI chosen is marked in yellow outline. Figure 1b shows the magnified region of the suspected tumor. Figure 2a shows images reconstructed using CS and ROICS methods at chosen acceleration factors of 5x, 10x, 15x and 20x. It can be observed that as the acceleration increases, artifacts in the images reconstructed using CS increases whereas ROICS reconstructed images were able to retain information even at an acceleration factor of 20x. Figure 2b and Figure 2c represent PK maps (K^{trans} and Ve qualitative maps respectively) obtained from CS and ROICS reconstructed images. It can be observed in the PK maps that ROICS performs better than conventional CS method and the significant error in performance increases in CS for 5x acceleration factor onwards whereas it is relatively lesser for ROICS. Reconstruction error using CS and ROICS are quantified using NRMSE values at chosen acceleration factors of 2x, 5x, 10x, 15x, 20x as shown in Figure 3. Graph depicts that for the conventional CS method, NRMSE value beyond 5x acceleration onwards shows a significant increase compared to ROICS.

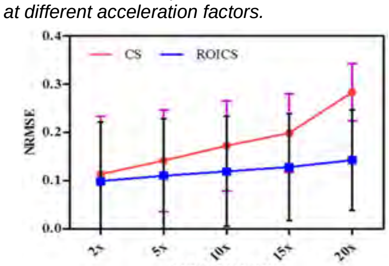

Figure 3: NRMSE for CS and ROICS at chosen acceleration factors

Conclusion and Future Work: The application of ROICS on breast DCE MRI data has been performed for the first time. It has been shown that qualitatively and quantitatively ROICS outperforms the conventional CS method. Current and future work involves radiological evaluation of CS and ROICS reconstructed DCE-MRI data.

References: [1] Quantitative MRI of the brain: measuring changes caused by disease. John Wiley, (2003), [2] Lustig et al., MRM 58.6 (2007):1182-1195, [3] Amaresha Shridhar Konar et al., p.3801, ISMRM (2013), [4] Amaresha Shridhar Konar et al.,IISc 94.4 (2014), [5] Chen Liyong et al., Magnetic resonance imaging 28.5 (2010), [6] michallenges.org/dcechallenge2/clinical.html